Use of Adaptive Fuzzy Systems in Parameter Tuning of Sliding-Mode Controllers

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***Abstract*—Soft computing methodologies, when used in combination with sliding-mode control (SMC) systems, aim to alleviate implementation difficulties of SMCs or to intelligently tune the controller parameters. In this paper, it is proposed to combine adaptive fuzzy systems with SMCs to solve the chattering problem of sliding-mode control for robotic applications. In the design of the controller, special attention is paid to chattering elimination without a degradation of the tracking performance. Furthermore, the *a priori* knowledge required about the system dynamics for design is kept to a minimum. The paper starts with a consideration of basic principles of sliding-mode and fuzzy controllers. Implementation difficulties and most popular solutions are then overviewed. Next, the design of a SMC reported in the literature is outlined and guidelines for the selection of controller parameters for the best tracking performance without chattering are presented. A novel approach based on the introduction of a "chattering variable" is developed. This variable, as a measure of chattering, is used as an input to an adaptive fuzzy system responsible for ringing minimization. On-line tuning of parameters by fuzzy rules is carried out for the SMC and experimental results are presented. Conclusions are presented lastly.**

***Index Terms*—Adaptive fuzzy systems, manipulator trajectory control, sliding-mode control (SMC).**

I. Introduction

ROBOTIC manipulator trajectory control is a challenging problem due to the coupled and nonlinear system dynamics involved. An additional difficulty arises due to the fact that system parameters may vary with time. In the face of these difficulties, the use of sliding-mode control (SMC) [1], [2] has often been proposed as a robust control strategy.

The primary characteristic of a variable-structure system (VSS) is that the control signal is discontinuous, switching on one or more manifolds in state space. The structure of the feedback system is altered as the state crosses each discontinuity surface. When certain conditions are met, all motions in the neighborhood of the manifold are directed toward the manifold and, thus, a sliding motion on a predefined subspace of the state-space is established in which the system state repeatedly crosses the switching surface [3]. This mode is a good candidate for tracking control of uncertain nonlinear systems. It has useful invariance properties in the face of uncertainties in the plant model. For single-input systems in controller canonical form, the theory of VSS is well developed. Motion control, especially robotics, has been an area that has attracted particular attention and many publications have appeared in the literature [4]–[7]. Also, a number of works are reported on the discrete time implementation and stability analysis of sliding-mode controllers [8]–[13]. Reference [13] suggests that the continuous time stability considerations can be still valid for discrete-time systems, provided that the sampling period is chosen short enough.

A pure SMC suffers from the following drawbacks in practical applications. Firstly, high frequency oscillations of the controller output, termed as chattering, introduce a problem. The high speed (ideally at infinite frequency) switching necessary for the establishment of a sliding mode causes the oscillations. A thorough explanation of the problem and what may cause it is given in a recent publication [2]. In practical implementations, chattering is highly undesirable because it may excite unmodeled high frequency plant dynamics and this can result in unforeseen instabilities. The second drawback is that, a SMC is extremely vulnerable to measurement noise. The input depends on the sign of a measured variable which is very close to zero, and this is where measurement noise enters the scheme with adverse effects. Thirdly the SMC may employ unnecessarily large control signals to overcome the parametric uncertainties. Another very important problem is difficulty in the calculation of the so-called equivalent control. A thorough and accurate knowledge of the plant dynamics is necessary for this purpose [14].

To overcome these problems, many modifications to the original sliding-control law have been suggested [15]. The most popular modification is the boundary layer approach, which is, basically, the application of a high gain feedback when the motion of the system reaches ε-vicinity of a sliding manifold [5], [14]. This approach is based on the idea of the equivalence of the high gain systems and the systems with sliding modes [16]. Another variation of the scheme is called "provident control." Provident control combines variable structure control and variable structure adaptation and performs hysteretic switching between the structures so as to avoid a sliding mode [17]. The computation of the equivalent control plays a vital role in both methodologies, requiring a good mathematical model of the plant.

With the development of the "intelligent control" field, many new control approaches based on fuzzy logic, neural networks, evolutionary computing, and other techniques adapted from artificial intelligence have come into common use. These methodologies provide an extensive freedom for control engineers to exploit their understanding of the problem, to deal with problems of vagueness, uncertainty or imprecision, and to learn

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by experience [18]–[20]. Therefore, they are good candidates for alleviating the problems associated with SMCs discussed above.

Fuzzy control systems, as tools against the problems of uncertainty and vagueness, incorporate human experience into the task of controlling a plant. When employed in robotic trajectory control, they mainly play one of two roles in the controller structure. One of them is to compute the control signal by fuzzy rules. The other is to tune, adapt or schedule the parameters of other control mechanisms to accomplish better performance in face of uncertainties and different operating points.

A method to combine adaptive fuzzy systems with SMCs to solve the chattering problem of SMCs is proposed in this paper. In the suggested approach, a special attention is paid to chattering elimination without system performance degradation. Furthermore, the prior knowledge necessary about the system dynamics for controller design is kept to a minimum.

The second section outlines the design of a SMC method reported in the literature and its application to the control of a direct drive SCARA-type two degrees of freedom robotic arm.

The third section presents a novel approach based on the introduction of a "chattering variable," a measure of chattering, and using it as an input to an adaptive fuzzy system responsible for the chattering or ringing elimination. On-line tuning of SMC parameters by fuzzy rules is carried out. The objective is to satisfy a designer prescribed performance criterion based on the tradeoff between the performance degradation and ringing elimination. The proposed method is tested on a direct-drive SCARA robot, and experimental results are presented.

The conclusions are presented in the fourth section.

II. SMC

A number of approaches based on SMC methodology are proposed in the literature for trajectory control of robotic manipulators. An important problem in this context is chattering, that is, oscillatory motion about the sliding surface. In this section, an SMC approach, which eliminates chattering with suitable controller parameters is considered. However, the determination of this suitable set of parameters is one of the difficulties met in its implementation. In the next section, a fuzzy adaptation scheme is devised for the on-line adaptation of the parameters of this controller.

The SMC approach [21], [22] outlined in this section is applicable to nonlinear plants which are linear with respect to the control input. The controller is developed by combining the variable structure systems theory and Lyapunov design methods. It possesses the desirable properties of the sliding mode systems while avoiding unnecessary discontinuity of the control and, thus, eliminates chattering, when the controller parameters are set suitably. Implementation results [22] that have already appeared in the literature indicate that the approach results in good trajectory performance when the parameters are well tuned. It is seen during these studies that the tuning of the controller for the control problem at hand can be a difficult and demanding task.

The organization of the section is as follows. Firstly, the SMC algorithm is briefed. Next, the direct drive manipulator used as test bed is described and the application of the SMC to this manipulator is detailed.

A. SMC

The control is applicable for systems represented in the following form:

$$\dot{x}_1 = f_1(x_1, x_2) \tag{1}$$

$$\dot{x}_2 = f_2(x_1, x_2) + B(x_1, x_2)u + B(x_1, x_2)d_d(t). \tag{2}$$

In this state-space description $x_1 \in R^{n-m}$, $x_2 \in R^m$, $u \in R^m$, $rank(B) = m$. d_d represents the disturbance. We also have the information that the components of the control input and the derivative of x_2 are bounded with known bounds. The aim is to drive the states of the system into the set S defined by

$$S = \{x: \phi(t) - s_a(x) = s(x, t) = 0\}. \tag{3}$$

Here, x is the state vector obtained by augmenting x_1 and x_2. The function $\phi(t)$ is the time dependent part of the sliding function vector $s(x, t)$ and contains reference inputs to be applied to the controlled plant. On the other hand, $s_a(x)$ denotes the state dependent part of $s(x, t)$. Specifically,

$$s_a = G_1 x_1 + G_2 x_2 \tag{4}$$

where the matrix G_2 is of rank m.

The derivation of the control involves the selection of a Lyapunov function $V(s)$ and a desired form for $\dot{V}$, the derivative of the Lyapunov function.

The selected Lyapunov function is

$$V = s^T s/2. \tag{5}$$

Therefore,

$$\dot{V} = s^T \dot{s}. \tag{6}$$

It is desired that

$$\dot{V} = -s^T D s \tag{7}$$

where D is positive definite. Thus, the derivative of the Lyapunov function will be negative definite and this will ensure stability. The last two equations together lead to

$$s^T(Ds + \dot{s}) = 0. \tag{8}$$

A solution for the equation above is

$$(Ds + \dot{s}) = 0. \tag{9}$$

The expression for the derivative for the sliding function is

$$\dot{s} = \dot{\phi} - G_1 f_1 - G_2(f_2 + Bu + Bd_d). \tag{10}$$

And, therefore, when $(Ds + \dot{s}) = 0$, we have that

$$u = \underbrace{-d_d + (G_2 B)^{-1}[\dot{\phi} - G_2 f_2 - G_1 f_1]}_{u_{eq}} + (G_2 B)^{-1} Ds. \tag{11}$$

For robotic manipulators, the matrix B is the same as the inverse of the positive definite manipulator inertia matrix and G_2 has the rank m. Therefore, the existence of the inverse of the matrix $G_2 B$ is guaranteed. From (10) and (11) above, it can be noted that when the part of the control input in (11) designated by u_{eq} is applied to the system, the derivative of the sliding function s will be zero. Such a control is termed "equivalent control" in SMC terminology. Thus, the control input is

$$u = u_{eq} + (G_2 B)^{-1} Ds. \tag{12}$$

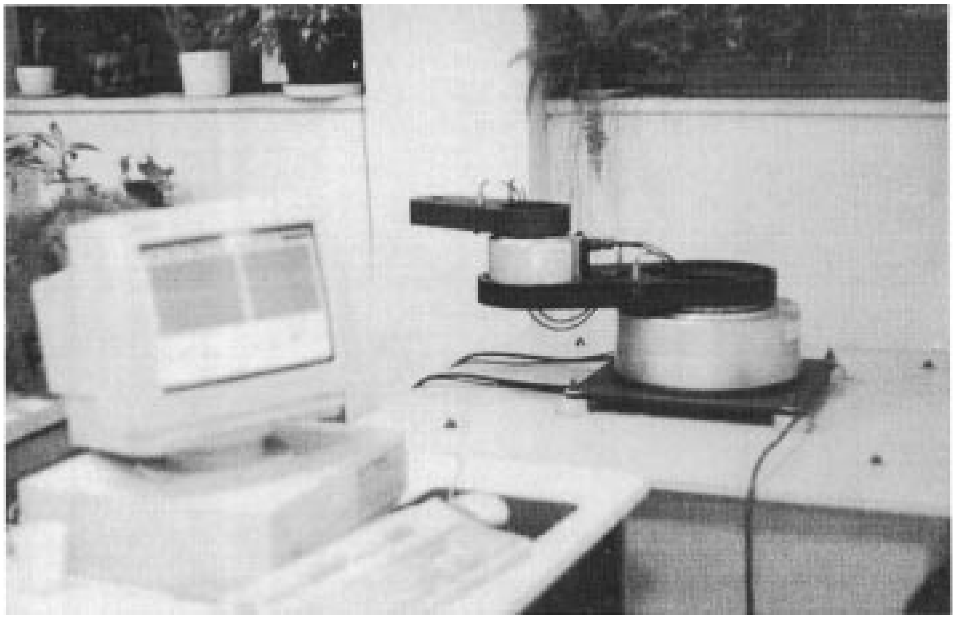

Fig. 1. The direct drive manipulator.

It is shown in [21] and [22] that the above equation can be put into the recursive form

$$u(t) = u(t^-) + (G_2 B)^{-1}(Ds + \dot{s})|_{t=t^-} \tag{13}$$

$$t^- = t - T \tag{14}$$

where $(G_2B_2)^{-1}(Ds + \dot{s})|_{t=t^-}$ is the updating term and T is a very small time interval corresponding to the sampling interval in digital implementation. On the sliding manifold, $u(t^-)$ becomes the same as the equivalent control. Since the control is bounded, the saturation function is added to the control law above

$$u(t) = \text{sat}\left(u(t^-) + (G_2 B)^{-1}(Ds + \dot{s})|_{t=t^-}\right). \tag{15}$$

The saturation function introduces some limits on the applicable reference state inputs and the tolerable parameter variations in plant dynamics. The controller in (15), unlike many other SMCs uses minimum knowledge about the plant. As will be seen in its application to the direct drive manipulator described in the next section, only an approximate information about the input gain suffices.

B. The Manipulator

The performance of the control algorithm presented above is checked by experimental investigations on a direct drive two degrees of freedom SCARA-type arm [23] shown in Fig. 1.

The dynamical equations of this manipulator are given by the following:

$$J(q)\ddot{q} + W(q, \dot{q}) + F = u. \tag{16}$$

In this expression q is the vector of joint angles q_1 and q_2. Also, u is the torque vector applied to the joints, J is the inertia matrix, W is the vector of centripetal and Coriolis forces, and F stands for Coulomb friction. The mass, length, and inertia parameters of the arm and the direct drive motors given in Table I in standard kg·m·s units.

A TMS320C30 floating point DSP based system is used to control the arm [23]. The user interface is on a general purpose computer. C language servo routines are compiled in this environment and downloaded onto the DSP. This approach enables the implementation of complicated intelligent control algorithms with reasonable sampling periods. In the case of simple algorithms, the use of sampling times in the range of 50–1000 μs is possible.

TABLE I
DYNAMICS PARAMETERS OF THE ROBOT ARM

Motor 1 Rotor Inertia	0.267	Arm 1 Length	0.359
Arm 1 Inertia	0.334	Arm 2 Length	0.24
Motor 2 Rotor Inertia	0.0075	Arm 1 CG Distance	0.136
Motor 2 Stator Inertia	0.040	Arm 2 CG Distance	0.102
Arm 2 Inertia	0.063	Axis 1 Friction	4.90
Motor 1 Mass	73.0	Axis 2 Friction	1.67
Arm 1 Mass	9.78	Torque Limit 1	245.0
Motor 2 Mass	3.0	Torque Limit 2	39.2
Arm 2 Mass	4.45		

The NSK torque motors used on base and elbow joints provide position signals with a resolution of 153 600 pulses/r.

C. Application of the Control Scheme to the Control of the Robot Arm

Consider the dynamical equations of the manipulator as given in (16) and select the angular positions and their derivatives as the states

$$q = x_1 \quad \text{and} \quad \dot{q} = x_2. \tag{17}$$

The following state equations are then obtained:

$$\dot{x}_1 = x_2 \tag{18}$$

$$\dot{x}_2 = \ddot{q} = J^{-1}(x_1)[u(t) - W(x_1, x_2) - F]. \tag{19}$$

From (19), it follows that

$$B = J^{-1}(x_1). \tag{20}$$

The design of the sliding surface can be carried out as follows. From (3), with the selection of state variables as in (17), we obtain

$$s = \phi(t) - s_a(q,\, \dot{q}). \tag{21}$$

The time dependent part of the sliding function is chosen as

$$\phi(t) = G_1 q_d + G_2 \dot{q}_d \tag{22}$$

where q_d is the desired position vector. Hence, with the definition in (4), it can be noted that s is a function of position and velocity errors. With the definition of position error as

$$e = \begin{pmatrix} e_1 \\ e_2 \end{pmatrix} = q_d - q \tag{23}$$

the following expression can be obtained for the sliding function s:

$$s(x,\, t) = \begin{pmatrix} s_1 \\ s_2 \end{pmatrix} = G_1 e + G_2 \dot{e}. \tag{24}$$

The matrices G_1 and G_2 used in this design are

$$G_1 = \begin{pmatrix} c_{11} & 0 \\ 0 & c_{22} \end{pmatrix} \equiv C, \qquad G_2 = \begin{pmatrix} 1 & 0 \\ 0 & 1 \end{pmatrix} \tag{25}$$

where c_{11} and c_{22} are positive constants. Here, the introduction of the matrix C is solely for notational simplicity.

From (20) and (25) we obtain that

$$(G_2 B)^{-1} = J(q). \tag{26}$$

Hence, the following control rule is obtained from (13) with a nominal inertia term J_n

$$u((k+1)T) = u(kT) + K J_n (Ds + \dot{s})|_{t=kT}. \tag{27}$$

Here, K is a diagonal gain matrix with positive entries used for tuning and D is chosen diagonal as well. The diagonal terms of the nominal inertia matrix J_n are calculated from an Euler–Lagrange model of the robot given in [23] with both joints at the zero position. The off diagonal terms are taken to be zero in order not to introduce incorrect coupling terms in the case of modeling errors. Thus, with the diagonal selection of the control parameter matrices above, an independent joint control mechanism is constructed.

In discrete time, the approximation below is used for the derivative of the sliding function

$$\dot{s}(kT) \approx \frac{s(kT) - s((k-1)T)}{T}. \tag{28}$$

In this expression, T is the control cycle time.

III. Adaptive Fuzzy Systems in Tuning SMC Parameters

An obvious difficulty in the implementation of the control scheme described in Section II is the selection of the controller parameters. In this section, fuzzy logic systems are employed to design an adaptation scheme for the sliding mode algorithm in [21], [22]. A measure of chattering is introduced and this measure together with the sliding variable function are the inputs to the fuzzy adaptation scheme by which controller parameters are tuned in real time.

The controller parameters which affect the system response are the entries of the C, D, and K matrices. Adaptation of these parameters is carried out in [24] with fixed fuzzy rules. During these studies it is observed that the most effective adaptation in chattering minimization is the one for the K parameters, whereas C and D adaptations play a secondary role.

The performance and robustness of the controller is affected by the selection of the gain matrix K. High gain can easily cause chattering whereas small values of the gains K_{kk} lead to the degradation of the tracking performance. In [24], a fuzzy adaptation algorithm is used which balances the chattering and error in the system and tunes the gain parameter in such a way to get the best tracking without chattering.

In this paper yet another novel approach is developed for the on-line tuning of K parameters using a measure of chattering. The method presented in this paper employs adaptive fuzzy systems represented as three-layer neural networks trained with back-propagation. The organization of the section is as follows. First, the so called "fuzzy identifiers" [25]–[27], which are used in the on-line tuning method, are introduced. Next, the application of the fuzzy identifiers for the SMC parameter tuning is presented. Experimental results constitute the final parts of the paper.

A. Fuzzy Identifiers

The fuzzy systems which are used in this chapter are of the following form:

$$h(\underline{v}) = \frac{\sum_{l=1}^{M} \overline{y}^{\,l} \left[\prod_{i=1}^{n} a_i^l \exp\left(-\left(\frac{v_i - \overline{v}_i^{\,l}}{\sigma_i^l} \right)^2 \right) \right]}{\sum_{l=1}^{M} \left[\prod_{i=1}^{n} a_i^l \exp\left(-\left(\frac{v_i - \overline{v}_i^{\,l}}{\sigma_i^l} \right)^2 \right) \right]}. \tag{29}$$

This function characterizes a fuzzy system with center average defuzzifier, product inference rule, singleton fuzzifier, and Gaussian membership functions. Here, M is the number of rules, $\underline{v}$ is the vector of input variables, $\overline{y}^{\,l}$ stands for the output constant of rule l, n is the number of input variables, v_i is the ith input variable, $\overline{v}_i^{\,l}$ is the center of the membership function for v_i for rule l, σ_i^l represents the width, and a_i^l the height of this membership function. Gaussian membership functions are differentiable. This feature is exploited in the back-propagation algorithm presented below. The function in (29) can be represented with a three-layer feed-forward neural network structure which is shown in Fig. 2 [25].

In Fig. 2, μ stands for the membership functions described above. Triangles represent gains.

With the motivation that systems of the form (29) are universal approximators [27], a back-propagation training algorithm for this class of fuzzy systems is developed in [25] as in the following.

For a given input–output pair $(\underline{v}^p,\, d)$ with $\underline{v}^p \in R^n$ and $d \in R$, a measure E of the modeling error of the fuzzy model $h(v)$ of the form introduced above in (29) can be defined by

$$E = \tfrac{1}{2}(h(\underline{v}^p) - d)^2. \tag{30}$$

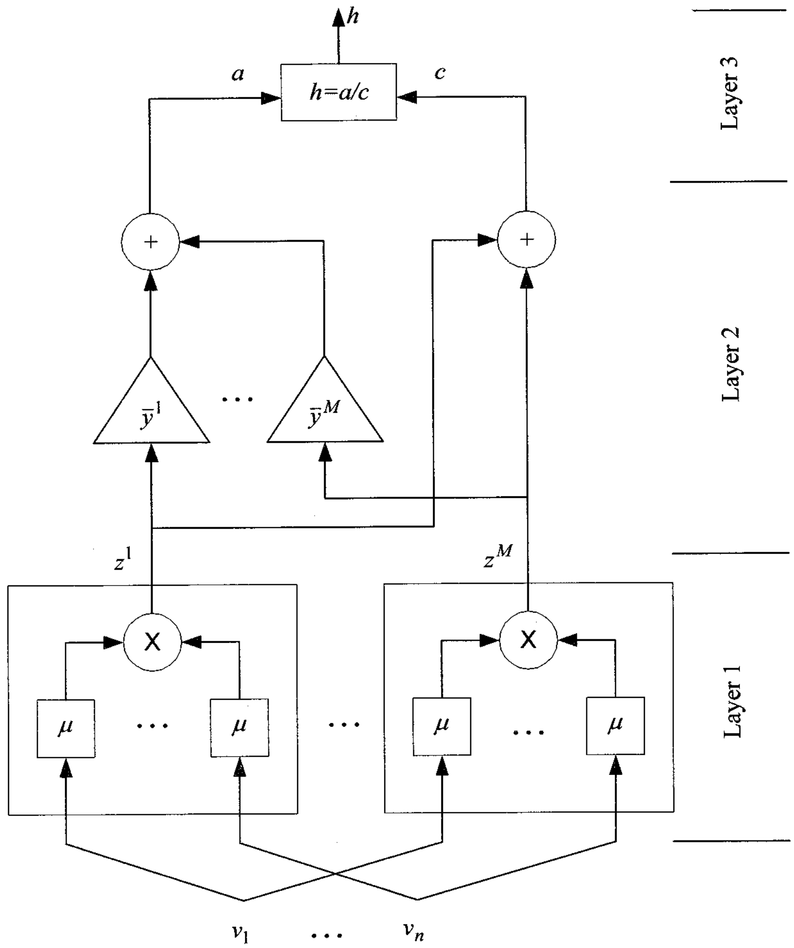

Fig. 2. The three-layer feed-forward NN architecture.

In order to minimize this error, assuming that all the a_i^l terms are equal to 1, fuzzy system parameters are varied according to the back-propagation rules which are as follows:

$$\overline{y}^{\,l}(k+1) = \overline{y}^{\,l}(k) - \alpha \left.\frac{\partial E}{\partial \overline{y}^{\,l}}\right|_k = \overline{y}^{\,l}(k) - \alpha \frac{h-d}{c} z^l \quad (31)$$

$$\begin{aligned}\overline{v}_i^l(k+1) &= \overline{v}_i^l(k) - \alpha \left.\frac{\partial E}{\partial \overline{x}_i^l}\right|_k \\ &= \overline{v}_i^l(k) - \alpha \frac{h-d}{c} (\overline{y}^{\,l} - h) z^l \, \frac{2(v_i^p - \overline{v}_i^l(k))}{\sigma_i^{l^2}(k)}\end{aligned} \quad (32)$$

$$\begin{aligned}\sigma_i^l(k+1) &= \sigma_i^l(k) - \alpha \left.\frac{\partial E}{\partial \sigma_i^l}\right|_k \\ &= \sigma_i^l(k) - \alpha \frac{h-d}{c} (\overline{y}^{\,l} - h) z^l \, \frac{2(v_i^p - \overline{v}_i^l(k))^2}{\sigma_i^{l^3}(k)}.\end{aligned} \quad (33)$$

Here α is a step size. The variable c is defined in Fig. 2, as the sum of rule truth values of the rules in the rule base, and h stands for the function $h(\underline{v}^p)$.

B. Application of Fuzzy Identifiers to On-Line Tuning of SMC Parameters

In this section, gain parameter tuning via the use of fuzzy identifiers is presented for the SMC method discussed in the previous chapter. The effects of the selection of gain parameter K are already discussed above. Based on this discussion, a new technique is developed for chattering minimization.

In this section, to compute the gain parameters, that is, the diagonal entries of the matrix K in (27), fuzzy systems of the form (29) with three rules per robot joint are constructed. In the approach presented in this paper, the absolute values of the sliding variables are used as the inputs to the fuzzy systems. Thus, the expression for the gain K_{kk}, $k = 1, 2$, is given by

$$K_{kk} = \frac{\sum_{l=1}^{3} \overline{y}_k^l \exp\left(-\left(\frac{|s_k| - \overline{s}_k^l}{\sigma_k^l}\right)^2\right)}{\sum_{l=1}^{3} \exp\left(-\left(\frac{|s_k| - \overline{s}_k^l}{\sigma_k^l}\right)^2\right)}. \quad (34)$$

In this expression, parallel to the discussion in Section III-A, $\overline{s}_k^l$ is the mean value of the Gaussian membership function describing the fuzzy set for $|s_k|$ in rule l and σ_k^l stands for the variance of this membership function. $\overline{y}_k^l$ is the output constant of rule l for robot joint k, and it represents the output value for K_{kk} in this rule. These parameters are set initially to obtain small values for K_{kk} when $|s_k|$ is small and large values when $|s_k|$ is large, in order to avoid chattering. This fuzzy system, without adapting its parameters $\overline{y}_k^l$, σ_k^l and $\overline{s}_k^l$ via back-propagation, performs to some extend in chattering minimization, if these parameters are set suitably. In order to end up with a suitable set of parameters many experiments based on trial and error should be carried out. Next, it is presented how the fuzzy system parameters are adapted exploiting a measure of chattering.

The back-propagation rules described above are employed for the on-line adaptation of the fuzzy system parameters. The term d in (30) is, however, unknown to the designer. That is, the desired value of the parameter K_{kk} for joint k, for admissible chattering (or ringing), cannot be known in advance. The goal of the adaptation is, for a given admissible ringing level, to determine a function which maps $|s_k|$ values to values of K_{kk}, in order to maintain that level of ringing in the control input.

A measure of chattering or ringing in control signal is used to devise a critic scheme for the adaptation of fuzzy system parameters, as given below. The chattering variable for joint k, Γ_κ, is defined as follows:

$$\Gamma_k(t) = \sum_{l=0}^{50} \rho_k(l) |u(t - lT) - u(t - (l-1)T)|. \quad (35)$$

In this expression T is the sampling period. The term $\rho_k(l)$ is described by

$$\rho_k(l) = \begin{cases} 0, & \text{if } (u_k(lT) - u_k((l-1)T)) \\ & \quad \cdot (u_k((l-1)T) - u_k((l-2)T)) \geq 0 \\ 1, & \text{if } (u_k(lT) - u_k((l-1)T)) \\ & \quad \cdot (u_k((l-1)T) - u_k((l-2)T)) < 0. \end{cases} \quad (36)$$

That is, $\rho_k(l)$ assumes the value 1 only if the difference in u_k changes its sign from control cycle $l-1$ to control cycle l. Only consecutive control input changes in opposite directions are accumulated in the variable.

The main structure of the tuning scheme is shown in Fig. 3. In the approach presented, the critic function is a fixed relation between the chattering variable Γ_k and the difference $h(v^p) - d$. This value is used in the (31)–(33) to update fuzzy system parameters. Specifically, introducing the admissible chattering or ringing level $\overline{\Gamma}_k$ for joint k, the critic function γ_k is selected as

$$\gamma_k = \frac{\Gamma_k - \overline{\Gamma}_k}{\overline{\Gamma}_k} \quad (37)$$

and the expression

$$K_{kk} - \overline{K}_{kk} = h(\underline{v}^p) - d = \gamma_k \quad (38)$$

is used in the back-propagation rules (31)–(33). In (38), $\overline{K}_{kk}$ stands for the specific gain value, which will assure the admissible ringing level $\overline{\Gamma}_k$. The admissible ringing level is a parameter to be determined by the controller designer. To assign the value of this parameter, the designer has to have some notion of how the parameter affects the controller performance and chattering. This notion can be acquired by numerous experiments with different values of the parameter. Although $\overline{K}_{kk}$ cannot be known in advance, the fuzzy identifier can be tuned with valuable information contained in γ_k. It can be noted that parameter change directions in the back-propagation laws are not changed by introducing the critic function γ_k. This is since ringing values above $\overline{\Gamma}_k$ mean that the value of K_{kk} is above the value of $\overline{K}_{kk}$. Similarly, ringing values below $\overline{\Gamma}_k$ mean that the value of K_{kk} is below the value of $\overline{K}_{kk}$. This follows from the discussion of the effects of the gain parameter on the ringing of the control signal, presented in the beginning of this section and constitutes the basis of parameter adaptation with the critic function.

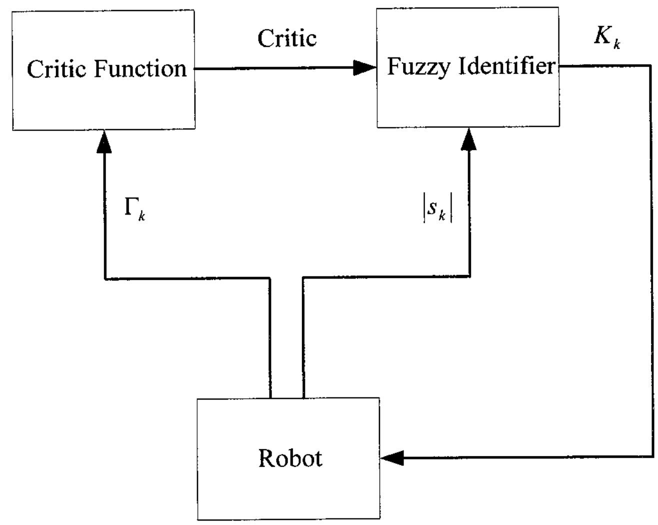

Fig. 3. The structure of the critic algorithm.

In the gain adaptation scheme presented above, the knowledge on the admissible error plays a secondary role and the role of the expert's knowledge on admissible chattering level is dominant. An admissible chattering level is given to the fuzzy logic system and the rest of the adaptation process is performed automatically. Introducing such a level of chattering is not a common practice in control applications. Therefore, many experimental studies have to be carried out by the control system designer in order to acquire information on the effects of the admissible chattering level and to use this parameter in an adequate way.

The structure developed above is similar to the Adaptive Neural Heuristic Critic Algorithm in [18], where two NNs are employed in places of the critic function and the fuzzy identifier in Fig. 3. The NN used in place of the critic function of Fig. 3 is called "Value NN" and the NN used in place of the fuzzy identifier is called "Action NN" in [18]. The value NN approximates evaluation functions, mapping states to expected values, and the role of the action NN is to generate a plausible action, mapping states to actions. Parameters of these two NNs are updated by back-propagation in an error minimization scheme where the error to be minimized is a function of reinforcement gathered from the external world.

The next section presents implementation results with the approach described above.

C. Experimental Results

A sampling period of 2 ms is used in the experiments. The learning rate α in (31)–(33) used in the experiments is a function of joint velocities. The learning rates for the two joints are expressed by

$$\alpha_k = \overline{\alpha}\dot{q}_k, \qquad k = 1, 2. \quad (39)$$

In this expression, $\overline{\alpha}$ is a constant which has the value 0.003 in the experiments, and $\dot{q}_k$ is the velocity of joint k. Weighting

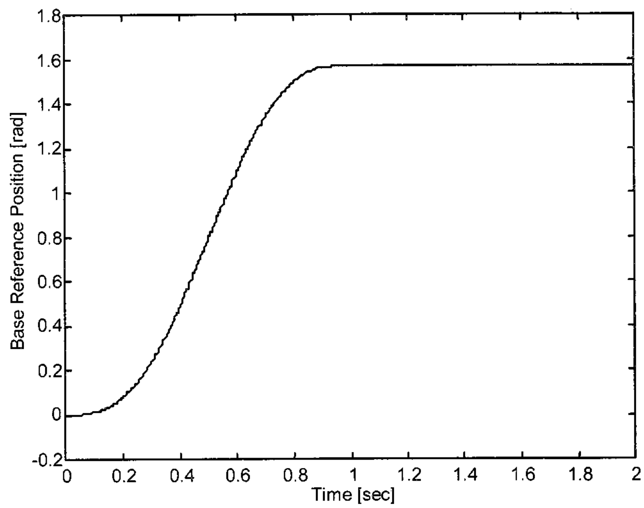

Fig. 4. Base reference position used in the experiments.

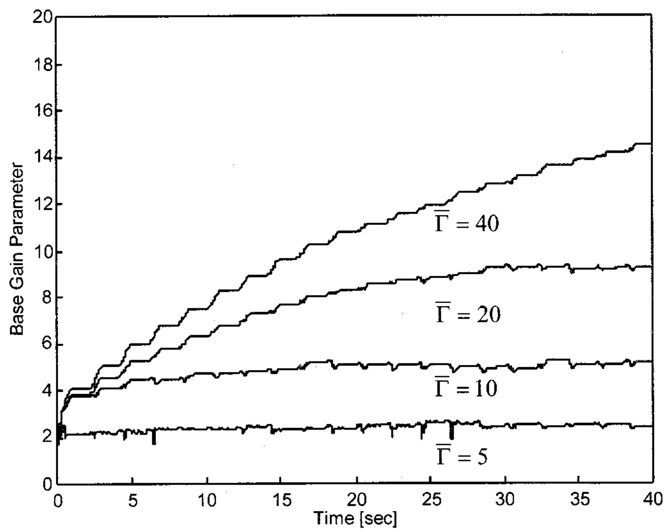

Fig. 5. Base gain parameters K_{11} for $\overline{\Gamma}_1 = 5$, 10, 20, and 40, respectively.

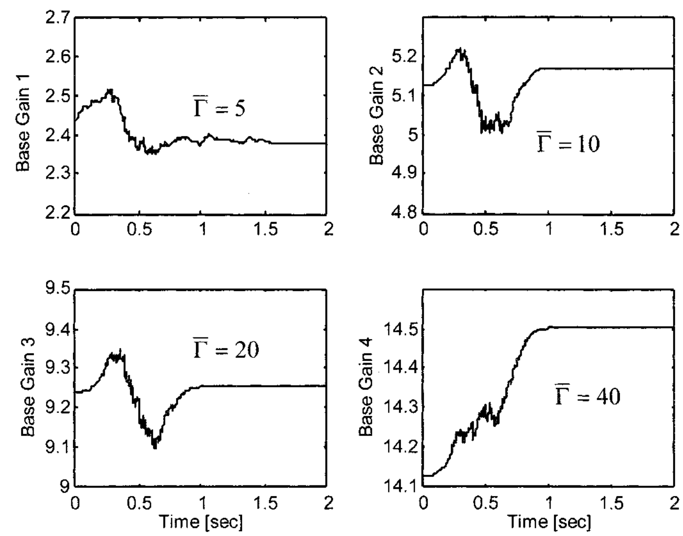

Fig. 6. Gain parameters K_{11} for $\overline{\Gamma}_1 = 5$, 10, 20, and 40, respectively, last 2 seconds.

the learning rate by joint velocities has the advantage that over-learning is avoided when the robot is stationary.

Four different values for the admissible chattering value $\overline{\Gamma}_k$ are tested for $k = 1$, 2, namely for the base and elbow simultaneously. The reference trajectory is shown in Fig. 4. Step reference inputs are avoided since they cause the manipulator system to face mechanical shock. This would result in a shorter lifetime for the bearings. Step references have been used in some other publications of the authors [24], however, in such cases, only very small step sizes are employed. To test the method with a scenario similar to the industrial use, smooth references covering a wider workspace are used. A similar reference curve is used for the elbow joint. The experimental results for this joint, due to lack of space, are not shown in this paper. However, the obtained results are similar to the ones presented for the base joint. The tested values for $\overline{\Gamma}_k$ are 5, 10, 20, and 40. Twenty consecutive runs are carried out with the reference trajectories with each of the $\overline{\Gamma}_k$ values mentioned. The gain parameters for the base are shown in Fig. 5. The total experiment time, which corresponds to 20 iterations with the reference position curve, is 40 s. It can be observed that the curves, except the one with $\overline{\Gamma}_k = 40$, converge in a few iterations to their final values. For $\overline{\Gamma}_k = 40$, that is for the curve labeled 4, no convergence is observed. This is because of the high level of ringing demanded by $\overline{\Gamma}_k = 40$. Fig. 5 indicates that, if a few more iterations were performed, these curve would also converge. However, the ringing level observed at the last run with $\overline{\Gamma}_k = 40$ has been large enough to stop experiments in order not to cause some possible damage to the robotic manipulator. Fluctuations in gain parameters after convergence are due to the fact that, not directly the gains but the fuzzy systems yielding them as a function of joint sliding variables are trained by the algorithm presented. The gain parameters in the last iteration, that is the 20th one, are shown in Fig. 6. In these figure, it can be observed how the gains are adjusted by the fuzzy systems represented by (34), as a function of joint sliding variables. In Fig. 6, "Base Gain 1," "Base Gain 2," "Base Gain 3," and "Base Gain 4" denote the gain parameters for base with $\overline{\Gamma}_k = 5$, 10, 20, and 40, respectively. Fig. 7 indicates the effects of different ringing levels $\overline{\Gamma}_k$ on the control signals. As can be seen from this figure, the control effort increases with increasing values of $\overline{\Gamma}_k$. The effects of $\overline{\Gamma}_k$ on the base position error are presented in Fig. 8. Error decreases with increasing $\overline{\Gamma}_k$. Considering Fig. 8, it can be concluded that the control method presented can be employed to accomplish a desired tradeoff level between chattering and performance degradation.

The method described in this paper resembles to the boundary layer approach in that the value of the gain is decreased when the system trajectory in the phase plane approaches the sliding line. Still, the value of the gain is large enough to be comparable with the gain value when the states are far away from the sliding line. Further in contrast with the boundary layer approach, the smoothness of the control signal is achieved by the formulation of the control law. The fuzzy system for gain determination is employed for further minimizing the ringing.

The method presented can be employed as an on-line tuning algorithm which is continuously ON. However, to test the performance of the system with the tuned controller parameters tuning

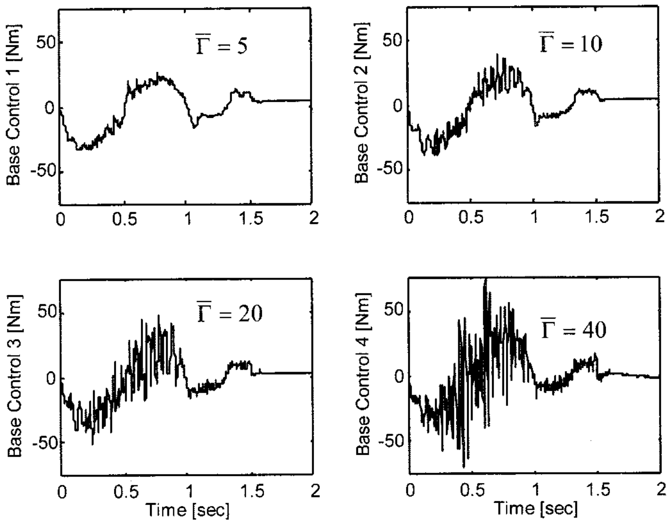

Fig. 7. Base control signals for $\overline{\Gamma}_1 = 5$, 10, 20, and 40, respectively, last 2 seconds.

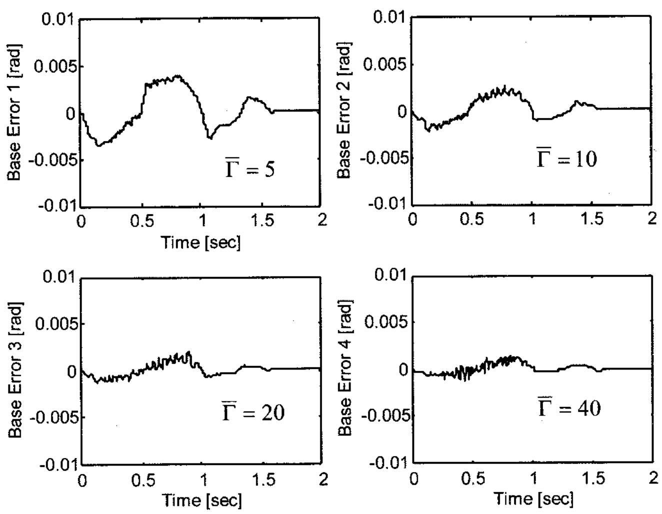

Fig. 8. Base errors for $\overline{\Gamma}_1 = 5$, 10, 20, and 40, respectively, last 2 seconds.

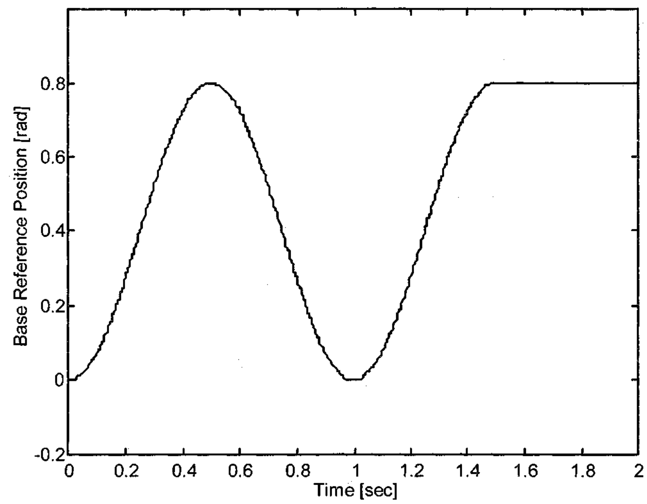

Fig. 9. Another position reference curve for the base joint.

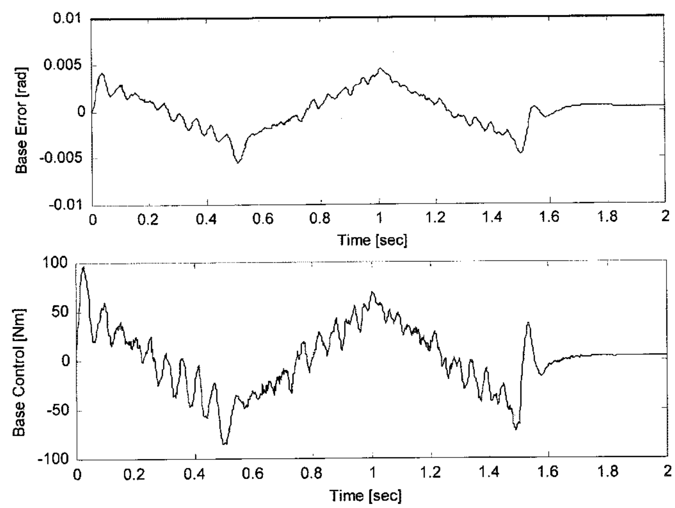

Fig. 10. Position error and control signals for the base joint with the reference trajectory in Fig. 9.

is turned OFF and additional experiments are carried out with different reference trajectories. One of the reference trajectories tested is shown in Fig. 9. Also in this case, good tracking performance with admissible ringing in the control signal are obtained as shown in Fig. 10, where the used value for $\overline{\Gamma}$ is 10.

As a note of implementation, in the following, the effect of longer sampling periods on the computation of the gain coefficient is discussed. If we fix the admissible chattering value and vary the sampling time, the following consideration will be useful. For longer sampling intervals, the change in the control signals is expected to be bigger from one control cycle to the other. As a result, we may end up with higher chattering variable values in (35). From (37), we can conclude that, the value of the critic function will be higher too. Considering the back-propagation algorithm, this will lead to a new gain curve which converges to a lower gain value in Fig. 5. As a remedy, the number of iterations can be adjusted according to the sampling period used in the specific system under control. In this way the chattering variable can be computed over the same time interval, however, over fewer control periods, if the sampling time is longer. As another solution, in the case of longer sampling intervals, higher admissible chattering values can be used in (37).

IV. CONCLUSIONS

The use soft computing methodologies in SMCs is getting more and more popular. In some studies the control structure is derived using the conventional design techniques and the computational intelligence is introduced in a complementary manner for a variety of purposes. The use of adaptation or learning by adaptive fuzzy systems, neural networks or by evolutionary computing complementary to SMCs are reported. They have the main objective of alleviating practical problems encountered in the implementation of SMCs. In the use of fuzzy logic in combination with SMC, such applications are termed as being indirect.

In this paper, a study of indirect methods in the fuzzy SMC of robotic manipulators is presented. As a novel approach, a control method based on on-line tuning of SMC parameters via the use of fuzzy identifiers and a measure of chattering is presented. In this approach, in which chattering elimination is the main concern, a critic function based on chattering is employed to train fuzzy systems. In the determination of the critic function, the knowledge that, controller gain and chattering change in the same direction, is exploited. A designer defined admissible ringing level is attained in the end of the on-line tuning process. The method eliminates the need for manual tuning, which is a time consuming task. The resulting control structure solves the chattering problem without degrading the trajectory tracking performance. Experimental studies with the method proposed indicate that it is successful in trajectory tracking, eliminating the need of plant dynamics information and alleviating the chattering problem. The method is implementable and successful in gain parameter tuning and, therefore, it is a good candidate for motion control applications.

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